

REMARKS

I. Introduction

In response to the Office Action dated March 28, 2008, which was made final, and in conjunction with the Request for Continued Examination (RCE) submitted herewith, claims 1, 8 and 15 have been amended. Claims 1-21 remain in the application. Re-examination and re-consideration of the application, as amended, is requested.

II. Prior Art Rejections

On pages (2)-(10) of the Office Action, claims 1-21 were rejected under 35 U.S.C. §102(e) as being anticipated by Cook, U.S. Patent No. 6,631,360 (Cook).

Applicants' attorney respectfully traverses these rejections.

- A. The cited portions of Cook do not teach or suggest "generating an input data set for the response model, wherein the input data set is generated using an Analytic Data Set Template containing one or more Analytic Variables that include both primitives that are base variables and conditions that are predicates, aggregates or other functions, wherein the primitives and conditions determine how the Analytic Variables are derived from operational data to produce the input data set, and wherein the Analytic Variables are subdivided into independent variables and their related dependent variables."

With regard to the above limitations found in Applicants' claims, the Office Action (in the "Response" section) asserts the following:

The Applicant argues that Cook does not teach "Analytical Variables that include both primitives that are base variables and conditions that are predicates, aggregates or other functions that describe how the Analytical Variables are derived from operational data". The Applicant further argues that the Office action assertion that Cook teaches said limitation is erroneous, because the claim recites that conditions are "predicates, aggregates or other functions that describe how the Analytical Variables are derived from operational data and classifying data in a category, according to the Applicant, does not teach these limitations. The Applicant further argues that the classification in Cook is performed first, and then a source of data for each defined category is defined. The Examiner answers that Applicant's specification only mentions said "condition" limitation in page 6 lines 15-32 where it recites "Analytical variables are comprised of primitives and conditions that describe how the Analytical Variable are derived from the operational data. Primitives are base variables, while conditions are predicates, aggregates or other functions." The

Applicant's specification page 6 gives an example, where it recites "for example "Sum of sales" in "Merchandise Department" during "Last 6 months" may identify hundreds of variables. However, the system could create an Analytical Variable by summing a "Sales" base variable (i.e. primitive) associated with multiple primitives (e.g. Department and Transaction Date variables) and conditions (e.g. Department = "Merchandise" and Transaction date > "February 1, 2001"). Thereafter, the user creates an Analytical Data Set Template containing the desired Analytical Variables required for a specific analysis task. Therefore, according to the Applicant's specification, said limitation of "Analytical Variables that include both primitives that are base variables and conditions that are predicates, aggregates or other functions that describe how the Analytical Variables are derived from operational data" simply means, according to Applicant's specification, selecting the Analytical variables from base variables by applying some type of condition selection to said base variables. Applicant's specification only recites "that conditions are predicates, aggregates or functions" and nothing else and Applicant's argues that Cook does not teach said claimed limitation by only reciting the claimed language without explaining the meaning of said claim language. Cook teaches selecting a base variable category (i.e. buyer/non-buyer) and applying some type of selection function to said data, which for example, is "n selected individuals' related data is removed from the training data structure" in order to create Analytical variables to be used in a density function for each category based on the training data structure with the selected individual's data removed" (see col 3, lines 30-40). Cook teaches applying conditions to primitive data (i.e. categories) in order to determine which analytical variables to use in order to predict if buyers/non buyers. Furthermore, Cook teaches that that data source may include independent (i.e. profile features such as buy or not buy) and dependent variables (i.e. category into which a profile individual falls) (see col 12, lines 10-30). Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

The portions of Cook cited by the Office Action as teaching these limitations "generating an input data set for the response model, wherein the input data set is generated using an Analytic Data Set Template containing one or more Analytic Variables that include both primitives that are base variables and conditions that are predicates, aggregates or other functions, wherein the primitives and conditions determine how the Analytic Variables are derived from operational data to produce the input data set, and wherein the Analytic Variables are subdivided into independent variables and their related dependent variables" are set forth below:

Cook: col. 3, lines 30-40 (actually, lines 27-47)

In accordance with other aspects of this invention, the training process involves identifying a data source for each category, establishing a training sample set and creating and storing a training data structure. After the training data structure is created and stored, the data structure is analyzed.

In accordance with further aspects of this invention, the training data structure is analyzed using a leaving-n-out approach. First a category is selected.

Next, n selected individuals' related data is removed from the training data structure. Then, a density function is estimated and a density value is calculated for each category based on the training data structure with the selected individual's data removed. The selected individual's data is reinserted into the training data structure and the foregoing sequence is repeated for another individual. After a density function has been estimated and a density value calculated for each category for each individual with the individual's data removed, the entire sequence is repeated for the next category. Processing continues until all categories have been analyzed. The value of n can vary from 1 up to half of the individuals comprising the training data structure.

Cook: col. 12, lines 5-30 (actually, lines 5-28)

FIG. 5 illustrates a training sample setup process 401 formed in accordance with the present invention. Initially, categories are selected 501. As noted above, selecting categories involves defining the categories and naming them, i.e., buyer/non-buyer, responder/non-responder, responder/non-responder/unsubscribe, sick/healthy, friend/foe, etc. Category names are normally entered into a computer system by a user via a graphical user interface (GUI), also called a dialog window. Next, for a selected category a data source is identified. The data source may be as simple as a manually preformatted file. Alternatively, and more likely, the data source is a source of data developed by profiling Internet customers. The data source must include independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls. The data may be collected, for example, by advertising a product to a selected group of potential purchasers whose profile is known to the advertiser. The buy or no-buy results, combined with the potential purchasers' profile features, creates the data source for the selected category, i.e., buy or no-buy. Next, a test 505 is made to determine if any more categories have been entered by the user. If so, the next category is selected and a data source is identified, which may be the same data source.

The above portions of Cook do not teach or suggest generating an input data set using an Analytic Data Set Template containing one or more Analytic Variables that include both primitives that are base variables and conditions that are predicates, aggregates or other functions, wherein the primitives and conditions determine how the Analytic Variables are derived from operational data to produce the input data set.

Instead, the above portions of Cook merely describe data that contains profile feature information (e.g., independent variables) regarding individuals that fall in the defined categories (e.g., dependent variables). However, Cook does not describe how this data is created, other than by "profiling" or "collecting," and merely states that "[t]he data source must include independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls."

Specifically, Cook does not use Analytic Data Set Templates to generate the data, Cook does not teach that Analytic Data Set Templates contain Analytic Variables, and Cook does not generate its input data sets from operational data using primitives and conditions of Analytic Variables contained within Analytic Data Set Templates.

B. The cited portions of Cook do not teach or suggest “splitting the input data set into a test sample and a validation sample.”

With regard to the above limitation found in Applicants' claims, the Office Action (in the “Response” section) asserts the following:

The Applicant argues that Cook does not teach “splitting the input data set into a test sample and validation sample”. The Examiner answers that the Applicant argues that Cook does not teach said claimed limitation by simply reciting the claimed language but without explaining said claimed language. Cook teaches identifying a data source (i.e. test sample) and a training sample (i.e. validation sample) (see col 12, lines 25-35). Furthermore, Cook teaches a validation sample when a decision array compares an individual true category to the category predicted by the selected interface engine (see col 11, lines 10-20). Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

The portions of Cook cited by the Office Action as teaching the limitations “splitting the input data set into a test sample and a validation sample” are set forth below:

Cook: col. 10, line 55 – col. 11, line 20

Returning to FIG. 4A, after the first inference engine is selected, a set of profile features are selected 409. This step is included so that independent variables (individual profile features) that are not different among categories can be eliminated. Preferably individual profile features are sorted based on standard statistics after controlling for multicollinearities. In addition to eliminating independent variables for which there is insufficient data for estimation, less significant individual profile features can also be eliminated if desired. The end result is one or more sets of profile features. At step 409 one set is selected.

After the inference engine and set of profile features have been selected, a training process is conducted 411. An example of a training process formed in accordance with the invention is illustrated in FIG. 6 and described below. In general, during the training process, various probability density functions are estimated for the selected engine and a data structure containing unbiased density values is created.

After the training process 411 is completed, a calibration process 413 is performed. An example of a calibration process formed in accordance with the invention is illustrated in FIG. 8 and described below. The calibration process creates a decision array in which are stored the results of classifying the individuals whose

individual profile features were contained in the training sample. As will be better understood from the following description, the decision array compares an individual's true category to the category predicted by the selected inference engine. The decision array in combination with the estimated density function and density value data structure contain all the algorithms and parameters necessary for implementation of the selected engine.

Cook: col. 12, lines 5-43

FIG. 5 illustrates a training sample setup process 401 formed in accordance with the present invention. Initially, categories are selected 501. As noted above, selecting categories involves defining the categories and naming them, i.e., buyer/non-buyer, responder/non-responder, responder/non-responder/unsubscribe, sick/healthy, friend/foe, etc. Category names are normally entered into a computer system by a user via a graphical user interface (GUI), also called a dialog window. Next, for a selected category a data source is identified. The data source may be as simple as a manually preformatted file. Alternatively, and more likely, the data source is a source of data developed by profiling Internet customers. The data source must include independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls. The data may be collected, for example, by advertising a product to a selected group of potential purchasers whose profile is known to the advertiser. The buy or no-buy results, combined with the potential purchasers' profile features, creates the data source for the selected category, i.e., buy or no-buy. Next, a test 505 is made to determine if any more categories have been entered by the user. If so, the next category is selected and a data source is identified, which may be the same data source.

After the data sources have been identified, a training sample set is established 507. This involves downloading data from the data source(s) and assembling the data into a computer file, or set of computer files, in a specific format, and storing the files in a workspace, i.e., in temporary memory. After establishing a training set in this manner, the downloaded data is converted into a training data structure having a predetermined configuration and the training data structure is stored in memory 509. A suitable training data structure is illustrated in FIG. 11. The profile features 1111a, 1111b, 1111c . . . 1111n of each individual 1113 in each category 1115 are included in the training data structure. As illustrated in FIG. 4A and discussed above, after the training data structure has been created, selected features of individuals may be eliminated. See step 409, FIG. 4A.

The above portions of Cook merely describe selecting a set of profile features as a training sample.

Nowhere does Cook describe splitting a data set. Instead, the training sample of Cook is developed independently, for example, of any validation sample.

Consequently, nothing in the above portions of Cook in any way teach or suggest that the set of profile features in Cook is generated by splitting an input data set comprised of Analytic Variables into a test sample and a validation sample.

- C. The cited portions of Cook do not teach or suggest "identifying independent and their related dependent variables using the test sample."

With regard to the above limitation found in Applicants' claims, the Office Action (in the "Response" section) asserts the following:

The Applicant argues that Cook does not teach "identifying related independent and dependent variables using the test sample". The Examiner answers that the Applicant argues that Cook does not teach said claimed limitation by simply reciting the claimed language but without explaining said claimed language. Cook teaches that that data source may include independent (i.e. profile features such as buy or not buy) and dependent variables (i.e. category into which a profile individual falls) (see col 12, lines 10-30). Therefore, contrary to Applicant's claimed invention, Cook teaches Applicant's claimed limitation.

The portions of Cook cited by the Office Action as teaching the limitations "identifying independent and their related dependent variables using the test sample" are set forth below:

Cook: col. 12, lines 5-45

FIG. 5 illustrates a training sample setup process 401 formed in accordance with the present invention. Initially, categories are selected 501. As noted above, selecting categories involves defining the categories and naming them, i.e., buyer/non-buyer, responder/non-responder, responder/non-responder/unsubscribe, sick/healthy, friend/foe, etc. Category names are normally entered into a computer system by a user via a graphical user interface (GUI), also called a dialog window. Next, for a selected category a data source is identified. The data source may be as simple as a manually preformatted file. Alternatively, and more likely, the data source is a source of data developed by profiling Internet customers. The data source must include independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls. The data may be collected, for example, by advertising a product to a selected group of potential purchasers whose profile is known to the advertiser. The buy or no-buy results, combined with the potential purchasers' profile features, creates the data source for the selected category, i.e., buy or no-buy. Next, a test 505 is made to determine if any more categories have been entered by the user. If so, the next category is selected and a data source is identified, which may be the same data source.

After the data sources have been identified, a training sample set is established 507. This involves downloading data from the data source(s) and assembling the data into a computer file, or set of computer files, in a specific format, and storing the files in a workspace, i.e., in temporary memory. After establishing a training set in this manner, the downloaded data is converted into a training data structure having a predetermined configuration and the training data structure is stored in memory 509. A suitable training data structure is illustrated in

FIG. 11. The profile features 1111a, 1111b, 1111c . . . 1111n of each individual 1113 in each category 1115 are included in the training data structure. As illustrated in FIG. 4A and discussed above, after the training data structure has been created, selected features of individuals may be eliminated. See step 409, FIG. 4A.

The above portions of Cook merely describe setting up a training sample by defining the categories, identifying a data source for a selected category (where the data source must include both independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls), and then downloading data from the data source to establish a training set.

However, there is no identification of independent and their related dependent variables being performed in these portions of Cook. Instead, Cook merely states that the data source "must include" independent variables, i.e., individual profile features and associated dependent variables, i.e., the category into which a profiled individual falls, without stating how the data is created, other than by "profiling" or "collecting."

D. The cited portions of Cook do not teach or suggest "identifying a Transformation Type for each of the identified independent and their related dependent variables."

With regard to the above limitation found in Applicants' claims, the Office Action (in the "Response" section) asserts the following:

The Applicant argues that Cook does not teach "identifying a transformation type, which is defined as a mathematical operation that provides the strongest association between the identified related independent variable and the dependent variable. The Examiner answers that Cook teaches probability density functions that result in normal or quadratic decision surfaces (see col 10, lines 1-10), where said density function is used to create a decision array (see col 3, lines 45-55) and where each element of the decision array there is a gain or loss (see col 14, lines 55-65) which shows an association between the identified related independent variables (i.e. individual profile features see col 10, lines 55-65) and the dependent variables (i.e. category into which a profile individual falls) (see col 12, lines 10-30). Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

The portions of Cook cited by the Office Action as teaching the limitations "identifying a Transformation Type for each of the identified independent and their related dependent variables" are set forth below:

Cook: col. 3, lines 45-55 (actually, lines 32-55)

In accordance with further aspects of this invention, the training data structure is analyzed using a leaving-n-out approach. First a category is selected. Next, n selected individuals' related data is removed from the training data structure. Then, a density function is estimated and a density value is calculated for each category based on the training data structure with the selected individual's data removed. The selected individual's data is reinserted into the training data structure and the foregoing sequence is repeated for another individual. After a density function has been estimated and a density value calculated for each category for each individual with the individual's data removed, the entire sequence is repeated for the next category. Processing continues until all categories have been analyzed. The value of n can vary from 1 up to half of the individuals comprising the training data structure.

In accordance with still further aspects of this invention, the calculated density values are used to create a density value data structure. Then, for each category and each individual, a decision rule is applied to the density value data structure for the individual. The results are used to create a decision array. After completion, the decision array is displayed so that a user can determine if the objective has been met.

Cook: col. 10, lines 1-10 (actually, col. 9, line 56 – col. 10, line 10)

After the objective has been set, a first inference engine is selected at 407. As will be better understood from the following description, the invention is architected with Bayes Rule as a framework. This allows any "inference engine" to be formalized in the same context. Bayes Rule effectively says that for a particular individual observation, that observation should be assigned to the category to which the observation has the maximum probability of belonging. The values of the independent variables, i.e., the individual profile features, are used to calculate these probabilities using a variety of inference engines. The inference engines are, in effect, algorithms that make the assumption that independent variables for a given category are distributed according to some probability density function. The most accurate inference engine will typically be the one for which the data are most closely modeled by the assumed probability density function. The presently preferred probability density functions are (a) normal with equal variances among categories that results in a linear decision surface, (b) normal with unequal variances among categories that results in a quadratic decision surface, and (c) Parzen that results in a polynomial decision surface.

Cook: col. 10, lines 55-65 (actually, col. 9, line 56 – col. 10, line 10)

Returning to FIG. 4A, after the first inference engine is selected, a set of profile features are selected 409. This step is included so that independent variables (individual profile features) that are not different among categories can be eliminated. Preferably individual profile features are sorted based on standard statistics after controlling for multicollinearities. In addition to eliminating independent variables for which there is insufficient data for estimation, less significant individual profile features can also be eliminated if desired. The end result is one or more sets of profile features. At step 409 one set is selected.

Cook: col. 12, lines 10-30 (actually, col. 12, lines 5-43)

FIG. 5 illustrates a training sample setup process 401 formed in accordance with the present invention. Initially, categories are selected 501. As noted above, selecting categories involves defining the categories and naming them, i.e., buyer/non-buyer, responder/non-responder, responder/non-responder/unsubscribe, sick/healthy, friend/foe, etc. Category names are normally entered into a computer system by a user via a graphical user interface (GUI), also called a dialog window. Next, for a selected category a data source is identified. The data source may be as simple as a manually preformatted file. Alternatively, and more likely, the data source is a source of data developed by profiling Internet customers. The data source must include independent variables, i.e., individual profile features and an associated dependent variable, i.e., the category into which a profiled individual falls. The data may be collected, for example, by advertising a product to a selected group of potential purchasers whose profile is known to the advertiser. The buy or no-buy results, combined with the potential purchasers' profile features, creates the data source for the selected category, i.e., buy or no-buy. Next, a test 505 is made to determine if any more categories have been entered by the user. If so, the next category is selected and a data source is identified, which may be the same data source.

After the data sources have been identified, a training sample set is established 507. This involves downloading data from the data source(s) and assembling the data into a computer file, or set of computer files, in a specific format, and storing the files in a workspace, i.e., in temporary memory. After establishing a training set in this manner, the downloaded data is converted into a training data structure having a predetermined configuration and the training data structure is stored in memory 509. A suitable training data structure is illustrated in FIG. 11. The profile features 1111a, 1111b, 1111c ... 1111n of each individual 1113 in each category 1115 are included in the training data structure. As illustrated in FIG. 4A and discussed above, after the training data structure has been created, selected features of individuals may be eliminated. See step 409, FIG. 4A.

Cook: col. 14, lines 55-65

As will be readily appreciated by those skilled in the art to which this invention pertains, in the real world, each category will have associated benefits and costs. These benefits may be tangible, as in the case of dollars, or intangible, as in the case of goodwill. Thus, for each element of the decision array there is a gain or loss that can be assigned to each individual within that element. The net gain or loss for each element of the decision array is the individual gain or loss multiplied by the number of individuals assigned to that element. The objective function is thus the sum of these net gains or losses.

The above portions of Cook merely describe the inference engines as algorithms that make the assumption that independent variables for a given category are distributed according to some probability density function, and that the best inference engine is determined, using the training sample, based on an estimated Gaussian density function. As described in Cook, the estimated

Gaussian density function estimates the proportions of selected subpopulations in a larger population, e.g., the frequency of occurrence of the independent variable in a category.

However, the estimated Gaussian density function of Cook is not a Transformation Type, which is defined as a mathematical operation that provides the strongest association between the identified independent variables and their related dependent variables. Specifically, Cook's estimated density function relates to the "distribution" of independent variables among categories, but not "why" (mathematically) an independent variable is associated with a particular category, as defined by Applicants' Transformation Type.

E. The cited portions of Cook do not teach or suggest "estimating a Coefficient for each of the identified independent and their related dependent variables."

With regard to the above limitation found in Applicants' claims, the Office Action (in the "Response" section) asserts the following:

The Applicant argues that Cook does not teach "estimating a coefficient for the identified related independent and dependent variables". The Examiner answers that the Applicant argues that Cook does not teach said claimed limitation by simply reciting the claimed language but without explaining said claimed language. Cook figures 12 and 13 teach estimating coefficients (i.e. density value) for each independent and dependent variable of said graph. Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

The portions of Cook cited by the Office Action as teaching the limitations "estimating a Coefficient for each of the identified independent and their related dependent variables" are set forth below:

Cook: FIGS. 12 and 13

CATEGORY	INDIVIDUAL	ESTIMATED RELATIVE DENSITY VALUES FOR EACH CATEGORY			
		CATEGORY A	CATEGORY B	...	LAST CATEGORY
CATEGORY A	1				
CATEGORY A	2				
CATEGORY A	...				
CATEGORY A	N				
CATEGORY B	1				
CATEGORY B	2				
CATEGORY B	...				
CATEGORY B	N				
...	...				
LAST CATEGORY	1				
LAST CATEGORY	2				
LAST CATEGORY	...				
LAST CATEGORY	N				

Fig. 12

PREDICTED CATEGORY	TRUE CATEGORY			
	CATEGORY A	CATEGORY B	...	LAST CATEGORY
CATEGORY A				
CATEGORY B				
...				
LAST CATEGORY				

Fig. 13

INDIVIDUAL	PROFILE FEATURES			
	FEATURE 1	FEATURE 2	FEATURE 3	...
1				
2				
...				
N				

Fig. 14

The above portions of Cook merely describe estimated relative density values for each category, namely the frequency of occurrence of independent variables in the categories.

However, the estimated relative density values of Cook are not Coefficients, which are defined as a relative measure (e.g., a weight) of the identified independent and their related dependent variables' contributions to a likelihood of response.

- F. The cited portions of Cook do not teach or suggest "generating a Model Equation for each of the identified independent and their related dependent variables using the identified Transformation Type and estimated Coefficient."

With regard to the above limitation found in Applicants' claims, the Office Action (in the "Response" section) asserts the following:

The Applicant argues that Cook does not teach "a model equation". The Examiner answers that the Applicant argues that Cook does not teach said claimed limitation by simply reciting the claimed language but without explaining said claimed language. Cook teaches a inference engine, which are algorithms that calculate how independent variables for a given category are distributed according to some probability density function (see col 10, lines 1-10). Therefore, contrary to Applicant's argument, Cook teaches a "model equation".

The portions of Cook cited by the Office Action as teaching the limitations "generating a Model Equation for each of the identified independent and their related dependent variables using the identified Transformation Type and estimated Coefficient" are set forth below:

Cook: col. 10, lines 1-10 (actually, col. 9, line 56 – col. 10, line 10)

After the objective has been set, a first inference engine is selected at 407. As will be better understood from the following description, the invention is architected with Bayes Rule as a framework. This allows any "inference engine" to be formalized in the same context. Bayes Rule effectively says that for a particular individual observation, that observation should be assigned to the category to which the observation has the maximum probability of belonging. The values of the independent variables, i.e., the individual profile features, are used to calculate these probabilities using a variety of inference engines. The inference engines are, in effect, algorithms that make the assumption that independent variables for a given category are distributed according to some probability density function. The most accurate inference engine will typically be the one for which the data are most closely modeled by the assumed probability density function. The presently preferred probability density functions are (a) normal with equal variances among categories that results in a linear decision surface, (b) normal with unequal variances among categories that results in a quadratic decision surface, and (c) Parzen that results in a polynomial decision surface.

Cook: col. 13, lines 5-45

As noted above, FIG. 7 illustrates a density function and density value calculating process 605 suitable for use in the process illustrated in FIG. 6 formed in accordance with the invention. First, a category is selected 701 by, for example, setting a pointer to the memory location of the data associated with the selection--in this case, the first category. Then, the density function for the category is estimated 703. More specifically, the parameters for the density function for the selected category are estimated from the training data structure (FIG. 11). For example, in the case where a Gaussian density function is used, the mean for each selected feature (FIG. 11) and the variance-covariance matrix for these features are estimated within each category (FIG. 11). These estimates become the parameter values in the estimated Gaussian density function for each category. In this estimated Gaussian density function, there exists a variable for each selected feature. The thusly created estimated density function is stored 705. Then, the estimated density function for the selected category is used to calculate an estimated relative density value for the selected individual in the selected category 707. More specifically, using the foregoing

example, the values of the selected features are substituted for the variables in the estimated Gaussian density function and a scalar is obtained. The result is used to create a density value data structure, which is stored 709. Then a test 711 is made to determine if any more categories exist. If more categories exist, the process is repeated. As will be recalled, the process illustrated in FIG. 7 occurs after the training data structure has been updated by removing a selected individual from a selected category. Thus, the density value data structure is for a selected individual in a selected category with the n individuals' data removed. An example of a density value data structure is shown in FIG. 12. For each category 1211 an estimate of the likelihood that each individual 1213 will fall in each category 1215a, 1215b . . . 1215n is included in the data structure.

The above portions of Cook merely describe inference engines as algorithms that make the assumption that independent variables for a given category are distributed according to some probability density function, and that the best inference engine is determined, using the training sample, based on an estimated Gaussian density function. As described in Cook, the estimated Gaussian density function estimates the proportions of selected subpopulations in a larger population, e.g., the frequency of occurrence of the independent variable in a category.

In addition, the above portions of Cook merely describe that a category is selected, the parameters for the density function for the selected category are estimated from the training data (in the case where a Gaussian density function is used, the mean for each selected feature and the variance-covariance matrix for these features are estimated within each category), and then the estimated density function for the selected category is used to calculate an estimated relative density value for a selected individual in the selected category (the values of the selected features are substituted for the variables in the estimated Gaussian density function and a scalar is obtained).

However, nowhere does Cook describe generating a Model Equation using a Transformation Type and a Coefficient. As defined in Applicants' specification, a Model Equation is a mathematical representation of the association of independent variables and their related dependent variables, a Transformation Type is a mathematical operation that identifies the association between the independent variables and their related dependent variables, and a Coefficient is a relative measure of the independent variables and their related dependent variables' contributions to a likelihood of response.

Thus, Cook refers to a density function, i.e., a function describing the "density" of a variable at a point, e.g., the frequency of occurrence of a variable at a point. As noted above, this means that Cook's density function relates to the "distribution" of independent variables among categories (dependent variables), whereas Applicants' Model Equation relates to "why" (mathematically) an

independent variable is associated with a particular dependent variable. Consequently, Cook does not describe generating the same Model Equation as recited in Applicants' claims.

G. The cited portions of Cook do not teach or suggest "validating the generated Model Equation by applying it to the validation sample."

With regard to the above limitation found in Applicants' claims, the Office Action (in the "Response" section) asserts the following:

The Applicant argues that Cook does not teach "validating the generated Model Equation by applying it to validation sample". The Examiner answers that the Applicant argues that Cook does not teach said claimed limitation by simply reciting the claimed language but without explaining said claimed language. Cook teaches performing a calibration process to determine the accuracy of a forecast (see col 11, lines 5-20). Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed invention.

The portions of Cook cited by the Office Action as teaching the limitations "validating the generated Model Equation by applying it to the validation sample" are set forth below:

Cook: col. 11, lines 5-20

After the training process 411 is completed, a calibration process 413 is performed. An example of a calibration process formed in accordance with the invention is illustrated in FIG. 8 and described below. The calibration process creates a decision array in which are stored the results of classifying the individuals whose individual profile features were contained in the training sample. As will be better understood from the following description, the decision array compares an individual's true category to the category predicted by the selected inference engine. The decision array in combination with the estimated density function and density value data structure contain all the algorithms and parameters necessary for implementation of the selected engine.

The above portions of Cook describe a calibration process, not a validation process. Calibration in Cook refers to a process that creates a decision array from the results of the training sample. Validation in Applicants' invention applies a Model Equation to a validation sample, which is created by splitting the input data set, after the Model Equation has been generated, using of the Transformation Type and Coefficient identified from the independent and dependent variables of the test sample.

- H. The cited portions of Cook do not teach or suggest "scoring customers retrieved from a database using the validated Model Equation as a customer promotion response model for use in customer relationship marketing."

With regard to the above limitation found in Applicants' claims, the Office Action (in the "Response" section) asserts the following:

The Applicant argues that Cook does not teach "scoring customers retrieved from a database using a Model Equation". The Examiner answers that the Applicant argues that Cook does not teach said claimed limitation by simply reciting the claimed language but without explaining said claimed language. Cook figures 12 and 13 teach determining the relative density value (i.e. score) for each individual category, feature and category. Therefore, contrary to Applicant's argument, Cook teaches Applicant's claimed limitation.

The portions of Cook cited by the Office Action as teaching the limitations "scoring customers retrieved from a database using the validated Model Equation" are set forth below:

Cook FIGS. 12 and 13

Fig. 12

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PREDICTED CATEGORY	TRUE CATEGORY			
	CATEGORY A	CATEGORY B	...	LAST CATEGORY
CATEGORY A				
CATEGORY B				
...				
LAST CATEGORY				

Fig. 13

PROFILE FEATURES					
INDIVIDUAL	FEATURE 1	FEATURE 2	FEATURE 3	...	LAST FEATURE
1					
2					
...					
N					

Fig. 14

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The above portions of Cook merely describe using the estimated density function for a selected category to calculate an estimated relative density value for a selected individual in the selected category. As noted previously, the estimated density function relates to the "distribution" of independent variables among categories (dependent variables).

As defined in Applicants' specification, a Model Equation is a mathematical representation of the association of independent variables and their related dependent variables, namely "why" (mathematically) an independent variable is associated with a particular dependent variable

Consequently, Cook does not describe the same Model Equation as recited in Applicants' claims.

I. Summary: Applicants' claimed invention is patentable over Cook.

In light of the above, Applicants' attorney submits that independent claims 1, 8, and 15 are allowable over Cook. Further, dependent claims 2-7, 9-14, and 16-21 are submitted to be allowable over Cook in the same manner, because they are dependent on independent claims 1, 8, and 15, respectively, and thus contain all the limitations of the independent claims. In addition, dependent claims 2-7, 9-14, and 16-21 recite additional novel elements not shown by Cook.

III. Conclusion

In view of the above, it is submitted that this application is now in good order for allowance and such allowance is respectfully solicited.

Should the Examiner believe minor matters still remain that can be resolved in a telephone interview, the Examiner is urged to call Applicants' undersigned attorney.

Respectfully submitted,


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